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# **CONTROL OF WIND TUNNEL OPERATIONS USING NEURAL NET INTERPRETATION OF FLOW VISUALIZATION RECORDS**

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## **SUMMARY**

Neural net control of operations in a small subsonic/transonic/supersonic wind tunnel at Lewis Research Center is discussed. The tunnel and the layout for neural net control or control by other parallel processing techniques are described. The tunnel is an affordable, multiuser platform for testing instrumentation and components as well as parallel processing and control strategies. Neural nets have already been tested on archival schlieren and holographic visualizations from this tunnel as well as recent supersonic and transonic shadowgraph. This paper discusses the performance of neural nets for interpreting shadowgraph images in connection with a recent exercise for tuning the tunnel in a subsonic/transonic cascade mode of operation. That mode was operated for performing wake surveys in connection with NASA's Advanced Subsonic Technology (AST) noise reduction program. The shadowgraph was presented to the neural nets as 60 by 60 pixel arrays. The outputs were tunnel parameters such as valve settings or tunnel state identifiers for selected tunnel operating points, conditions, or states. The neural nets were very sensitive, perhaps too sensitive, to shadowgraph pattern detail. However, the nets exhibited good immunity to variations in brightness, to noise, and to changes in contrast. The nets are fast enough so that ten or more can be combined per control operation to interpret flow visualization data, point sensor data, and model calculations. The pattern sensitivity of the nets will be utilized and tested to control wind tunnel operations at Mach 2.0 based on shock wave parameters.

## **INTRODUCTION**

There has been an investigation at Lewis Research Center of the use of artificial neural networks for controlling wind tunnel operations primarily from flow visualization. The work is being accomplished in a small subsonic/transonic/supersonic-to-Mach-4.0 wind tunnel. The 3.81 by 10 in. (0.0968- by 0.254-m) tunnel is a platform for testing instrumentation and components as well as parallel processing and control strategies.

Our expectation is that artificial neural networks in combination with workstations and the tunnel's data handling and control systems will utilize flow visualization patterns in a most convenient manner. Artificial neural networks can be trained in principle to map flow visualization patterns onto properties such as shock wave positions (ref. 1) or onto other parameters that characterize the tunnel's operating state.

The original intent was to use neural nets as sequencers, trained with an expert operator's examples. A sequencer maps flow visualization patterns, point sensor outputs, current control settings, model data, and other inputs onto the next tunnel operating state. The operating state is represented by sensor readings or control settings. In effect, the neural nets learn to compress data by example, without the use of physical models or theories. Our recent tests of this concept indicate that a hybrid control system that uses neural nets as one component is probably more suitable for meeting the expectations of our intent.

The limits, strengths, and weaknesses of the neural net approach have been tested to some extent with archival flow visualization records (ref. 2) (the tunnel has been operated occasionally since 1946).

The tunnel recently was reactivated, and shadowgraph was recorded at Mach 2 through the tunnel's 8 ft. (2.44 m) long optical windows for the first time since the 1950's. But, this report is concerned mainly with testing the neural net approach during recent operations of the tunnel as a three-blade, four-passage cascade at subsonic and transonic conditions. The cascade was used for wake surveys in connection with NASA's Advanced Subsonic Technology (AST) noise reduction program. Most of the tests were conducted without flow visualization and at a single flow condition; hence training sets could not be acquired. But, there was initially a cascade tuning phase where shadowgraph was used and where the tunnel was operated at a modest number of different conditions. Tuning requires adjustments of the tunnel roof and floor geometries and adjustments of the boundary layer bleeds. The operator attempts to equalize leading edge shock waves and compression bubbles, blade wakes, and Mach waves from the blades' trailing edges.

Tuning was a difficult challenge for the neural nets and would be for any flow-visualization-based approach to controlling operations. Tuning, in the first place, is an iterative procedure. In the operator's opinion, flow visualization was vital during the initial stages and inadequate during the final stages where pressure surveys of the passage flows were most useful. An automated system to emulate the operator's tuning exercise must adapt just as the operator does. A second complication is that the operator used expert knowledge from previous cascade tuning exercises (ref. 3). Expert knowledge was required to supplement unreliable pressure readings and unrepeatable control readings. In effect, tuning used a weakly defined, time varying mixture of flow visualization, pressure sensor readings, and expert knowledge.

A feed forward network should in principle still be able to learn such an exercise given enough training examples. In effect, all the pressure sensor data, flow visualization pictures, valve settings, etc. are mapped onto new valve settings, Mach numbers, or sensor readings. This blanket approach assumes that many inputs will be irrelevant at any moment. The net is expected to learn by example to ignore the irrelevant inputs and to learn the correct weightings of the other inputs. There is no way to quantify the size of the training set required; the training set probably should at least cover the input, output spaces of parameters uniformly. In practice, such a training set is likely to be impractically large. The practical approach is to discover where neural nets are most useful and to combine them in a hybrid system with other parallel processing paradigms such as rules and fuzzy logic to control operations.

This paper presents results only for the flow visualization records as inputs. This limited exercise serves to: introduce the wind tunnel setup which can be used affordably for research in the intelligent control of operations as well as other NASA projects (High Speed Civilian Transport (HSCT), AST, emissions testing, etc.); introduce the systems for data handling, neural computing, and control; and demonstrate the requirements, speed, and performance of neural nets for interpreting shadowgraph data recorded during the cascade tuning process. In particular, the software nets have shown more than adequate speed on a SGI Crimson workstation for current operations, rapid learning of shadowgraph to tunnel-state training records, good immunity to noise as well as changes in contrast and brightness, and good geometry sensitivity. But poor immunity to extraneous patterns and rotational or translational movements of the shadowgraph field leads to a requirement for careful control of these conditions or large training sets. The cascade mode of the wind tunnel is outlined in the next section. Then the system for neural net control of wind tunnel operations using neural net interpretation of flow visualization records is discussed. Finally, the results of training and testing the neural nets are presented. There is a brief discussion of future work for neural net control based on identification of shock-wave positions and shapes at Mach 2.0 to 4.0.

## WIND TUNNEL IN CASCADE CONFIGURATION

The cascade and tuning controls are described in abbreviated form. The objective is to list the key elements that affect flow visualization, since this paper is concerned primarily with the control of opera-

tions using neural net interpretation of flow visualization patterns. Detailed discussions of the cascade, its structure, its purpose, its sensors, its controls, and its future are outside the scope of this paper. All of these factors affect wind tunnel operations, but in ways too complex to be factored into the present neural net research.

The wind tunnel, which has been operated occasionally since 1946, is little more than a rectangular duct connected to an altitude exhaust system. The flat roof and floor segments are separated by 10 in. (0.254 m). The three-blade, four-passage cascade was inserted in the duct as shown in figure 1. The upstream end of the cascade insert is a bell-mouth flow conditioner through which atmospheric air enters. Optical access is provided through a 14 in. (0.356 m) long window. Shadowgraph or schlieren must be used in double-pass mode off a mirror attached to the rear wall of the cascade. A rear surface mirror is used for that purpose. The window, mirror combination definitely is not schlieren grade.

Figure 2 shows the details of the cascade insert. The actual flow passage is only 4.60- by 3.81-in. (0.117- by 0.0968-m). There are 3 airfoils or blades, and each blade has a chord of 3.00 in. (0.0762 m) and a span of 3.81 in. (0.0968 m). The three blades are staggered to emulate the blades of a rotating fan in turbomachinery. The roof and floor of the cascade are defined by tail-board, half-blade-flap combinations: the tunnel operator must adjust the passage heights and tail-board, half-blade-flap angles as part of the cascade tuning process. These adjustments have a significant effect on flow visualization, and were accomplished during the first three days of cascade tuning. The operator also adjusts boundary layer bleeds during the tuning process. The boundary layer bleeds are arranged in three groups: roof bleeds, floor bleeds, and a pair of sidewall bleeds. Both sidewall bleeds are opened the same percentage at all times. We shall simply refer to the roof, floor, and sidewall bleeds or bleed settings in subsequent discussions. Boundary layer bleed adjustments constitute fine tuning, and were accomplished during the final two days of cascade tuning. The effects on flow visualization are less, and wake pressure surveys were more useful than flow visualization during the final two days of cascade tuning. Ironically, we took the training examples for this report from the fourth day, when flow visualization was less effective. The reason was that we later attempted to repeat this part of the tuning process for comparison with the original. Finally, there is a traversing probe for wake pressure surveys and a fixed position Mach number indicator; both are downstream of the blades as indicated in figure 2.

There are two additional, significant controls. They are the valves EL 2403 and EL 2403 A shown connecting the duct to the altitude exhaust system in figure 3(a). Figure 3(b) summarizes the more than 40 parameters which are involved in the actual cascade tuning process. Only 6 are incorporated in the training sets discussed in detail later in this report.

The next section discusses how neural nets were incorporated in the cascade tuning exercise and how they will be incorporated in future work.

## SYSTEM FOR CONTROLLING WIND TUNNEL OPERATIONS WITH NEURAL NETWORKS

The general layout for controlling operations is shown in figure 4. All the elements for this layout exist, but are not fully interconnected at this time.

The SGI Crimson XS24 workstation is central for this report, but is to be regarded as an accessory module (slave) for operations. The artificial neural nets are implemented in software (some would say by emulation). The Crimson has VME slots to receive neural-net hardware, but hardware is not needed at the present stage of development. A commercial neural net package (ref. 4) is used for generation and training of the neural nets. The package supports menu generation, modification, and interrogation of a large variety of nets including several feed forward architectures and training algorithms. The package also supports rapid generation of parallelized C code for the trained nets. The compiled code can be linked with other code or combined with other software in a hybrid system for controlling operations.

Most of the data channels used for this study consist of pixels of flow visualization. The workstation receives flow visualization directly through a VME mounted video frame grabber. The video frame grabber is essentially a single-shot frame grabber which supports a large number of video standards. This investigation was performed with a CCD camera (ref. 5) and the NTSC standard. The CCD camera and similar array detectors can be used with many kinds of flow visualization such as interferometry, laser induced fluorescence, and schlieren. This study was performed with shadowgraph to minimize the window pattern. Some of the tunnel's windows are more than 50 years old and are definitely not schlieren free. To make matters worse, the shadowgraph was operated in double-pass mode off a back-surface sidewall mirror with a significant crack.

Shadowgraph was adequate for the shock-wave and wake visualizations required for the early stages of the cascade tuning exercise.

Images were captured and prepared for processing by the neural nets in the following way. A 646 by 486 pixel frame was grabbed by the frame grabber and stored in a file. The stored image was converted to black and white (8 bits) and cropped to 486 by 266 pixels. Figures 5(a) and 5(b) show samples of full and cropped images of a cascade flow condition. Cropping saves only the flow visualization field. The image was then converted to 60 by 60 pixels. Figure 5(c) shows the 60 by 60 pixel version of the sample. The neural net package can handle images as large as about 128 by 128 pixels. The operations are accomplished with standard workstation software. The 60 by 60 pixel images were then converted to binary for presentation to the compiled neural net.

Training, by contrast, requires that a desired output vector be appended to an image to form a training record. Records are then concatenated to form a training set. Training is accomplished, as discussed in the next section, with the menu driven portion of the neural net package.

There are at least three other kinds of data that can be used for controlling operations. These data include point sensor readings such as provided by pressure sensors, data generated from computational models, and control settings. Our intent is to supply the workstation with point sensors readings in either of two ways. Point sensor readings can be supplied rapidly through the RS232 ports of the workstation by the tunnel's distributed control system (Modicon in fig. 4)(ref. 6). That system is still being constructed, and drivers still must be written. The second way is to supply point sensor readings over the network using the central data acquisition system known as Escort D. Escort D can supply 800 channels of sensor data in ascii format and will be used at least temporarily for future work. Models can be used to compute input patterns for the neural networks. The simplest example would be to calculate shock-wave positions, angles, and shapes. The performance of the feed forward net is relatively insensitive to image contrast, so that simple two level images, computed for a large number of cases, might be adequate for training. Finally, control valve settings can be supplied by the Modicon distributed control system.

The expected performance of the layout of figure 4 can be described. In fact, only the flow visualization channels were hooked to the workstation for the work described in this report. Point sensor readings and control settings were read manually. The Escort D data handling system and the distributed control system were not available. Nevertheless, the timing limitations of the subsystems of the tunnel are known. The frame grabber required several seconds to acquire an image and create an image file. The update time for point sensor readings from Escort D is measured in seconds, and the tunnel operator's own responses are often measured in minutes. The operator's response is deliberately slow to prevent window damage. (The maximum pressure-change-rate must be less than 6 psi per min.) A software neural network, by contrast, was measured to process more than 300 of the 60 by 60 pixel images per second. There would be plenty of time for neural net processing, even if a 30 frame-per-second frame grabber could be used.

The natural inertia of wind tunnel operations allows plenty of time to use many neural nets per operation. In any case, the mix of inputs, and the nets in force, will vary from one stage of operations to the next. As stated in the introduction, the importance of flow visualization was high during the early stages

of cascade tuning, but was supplanted by wake surveys during later stages. The decision to change from one set of inputs to another is an expert decision, and might be accomplished best by a rule based hybrid. Perhaps, a master neural net might work. But, the neural nets, in effect, are being used as data compression devices. Each net is trained, or programmed in some way, to map a mix of inputs onto comparatively few control settings. The net-to-net architecture might vary depending on the inputs. Pressure settings are probably the best choices for outputs at present, since the settings of the tunnel valves cannot be read accurately or repeatably. The so-called master controller in figure 4 will poll the workstation periodically for appropriate settings. This particular approach should make good use of parallel processing and should interfere the least with current approaches to wind tunnel operations. In effect, the workstation will function as another slave module in the distributed control system.

The results of this study pertain to neural nets that use only flow visualization inputs. We suspect that control of wind tunnel operations using neural net interpretation of pure flow visualization records will work only for certain restricted operations. An example would be controlling the position, shape, or angle of a shock wave. The training and responses of neural nets, trained with the shadow-graph records from the cascade tuning exercise, are discussed in the next section.

## TRAINING

### Training Sets for Cascade Tuning

Most of this section discusses a training set formed from a small subset of the total tuning steps. Tuning required 5 separate runs in January, 1994. The tuning process also involved more than 40 parameters: parameters affecting roof and floor geometries (tail boards and flaps in fig. 2), Mach numbers, boundary layer bleed settings (figs. 2 and 3), valve settings (figure 3(a)), pressure rake positions (fig. 2), and pressure readings (fig. 3(b)). The actual utilization of each parameter varied greatly. The readings and settings of many parameters proved to be unreliable, as mentioned in the introduction.

Training sets initially were constructed from the shadowgraph and tunnel parameters from the first four tuning runs. There were 44 tunnel states recorded during these runs. The final tuning run (Run 5) involved extremely fine tuning and checking and was not used. Various kinds of training records were created. Inputs consisted mainly of shadowgraph. Outputs contained various combinations of actual tunnel parameters. The records were apportioned between training and test sets. The performance of the nets for predicting the test sets was passable only when the test set consisted of every other tunnel state. Predictions of test sets consisting of entire runs were inadequate.

The following problems with the training sets were identified subsequent to the January tuning runs. Some of the pressure readings, Mach numbers, and control settings were incorrect or inaccurate. The alignment of, and illumination pattern from, the shadowgraph changed significantly from one run to the next. There was a large vertical crack in the wall mirror whose appearance changed from one run to the next. The dirt patterns on the windows changed from run to run, where dirt originated from oil leaks and winter salt streaks. A traversing probe (fig. 2) appears at random locations in some of the frames. The training examples showed only a few changes for some parameters.

We decided to specialize on the fourth run to minimize the effects of variations in alignment, illumination, and dirt patterns. We also decided to repeat run 4, since that run did not require that the roof and floor geometries be changed. There were 21 states of the tunnel recorded during this run. Many of the states were essentially the same, differing in the position of the traversing probe. The inputs were the 60 by 60 pixel renditions of the shadowgraph as in figure 5(c). Leading edge bubbles and shock waves were visible at each blade along with trailing edge Mach waves and wakes as in figures 5(a) to 5(c). There were also streaks of salt on the window as well as a vertical crack in the mirror. The shadows of the three blades were visible. Some patterns were in the window itself. The pixel values ranged between 0 and 255.

They were normalized typically between 0 and 1 for presentation to the nets. There are in fact two forms of normalization. An individual pixel can be normalized for the range of values shown by that pixel in the training and test sets. Training sets normalized in this manner are learned most rapidly. But, the illumination pattern must not change, if the net is to be used to make predictions from new data. It is safer to normalize all the pixels as if the full range of values was always between 0 and 255.

Six of the more than 40 possible parameters were selected as outputs. These outputs were: the percent open reading of the main valve (2403 in fig. 3(a)) connecting the wind tunnel to the altitude exhaust; the percent open reading of a vernier control valve (2403 A in fig. 3(a)) bypassing the main valve; the percent open readings of the roof, floor, and sidewall boundary layer bleeds (fig. 2); and the downstream Mach number (fig. 2). Note again that the sidewall reading is actually the reading for each of two sidewall bleeds. These numbers were normalized, typically between 0.2 and 0.8 for sigmoid transfer functions.

There were only two settings of the main valve in the training set. They were 0 percent and 22 percent. The actual meanings of these numbers are questionable. The valve leaks in the closed position, for example. The setting for a given state might vary by 10 percent as altitude exhaust pressure varies. It would be more appropriate to call the readings valve state 1 and valve state 2, but the typical readings were retained for this study. There were 5 settings of the bypass valve. These settings were critical, but not accurately readable. A 5 percent variation was to be expected. Again, the actual numbers were retained in the training set, but should be interpreted as valve state settings. The roof bleed had 3 settings, the floor bleed had 2 settings, and the side wall bleed had 2 settings. Training in sequencer mode, as defined in the next paragraph, reduced the number of bypass valve and bleed settings by one. The Mach number ranged from about 0.5 to about 1.5. This range of Mach numbers was appropriate only for the tuning exercise. Subsequent operation of the cascade for wake surveys in connection with the AST program was subsonic.

The training sets were constructed in a sequencer mode. That is, the 6 parameters, which were appended to a shadowgraph pattern to form a training record, represented the next state of the tunnel rather than the current state. There were in fact only 7 distinct changes of the 6 parameters during tuning run 4. The traversing probe is in different positions for the repeated records. Another training set was constructed where only the required tunnel state change was identified. There were 7 outputs for the 7 changes of tunnel state, where an output is 1 only for the state change required by the input shadowgraph and 0 otherwise.

Aligning the shadowgraph for zero rotation or translation of the flow visualization image was found to be particularly difficult. The instrument was mounted on tires and was used with the broken mirror. In an attempt to train for alignment errors, 4 additional training records per original training record were constructed by translating the field 5 pixels along the positive and negative x and y directions. The training set then contained 100 records for 20 original run points. One of the original 21 records was discarded because the shadowgraph light source had moved during its recording.

We attempted to repeat tuning run 4 in May, 1994. The control system itself was not improved, but the reliability of the sensor readings was much improved. Laser velocimetry had been used to check some velocities. The flow visualization could not be duplicated, however. The relative blade positions had been distorted; the dirt patterns had changed from salt streaks on the windows to oil streaks on the mirror; and the mirror crack had changed. However, a training set which combined the January and May tuning exercises proved to be slightly more resistant to alignment errors as will be discussed.

The neural nets and their training are discussed in the next section.

### Neural Nets for Cascade Tuning

Several types of artificial neural nets were trained with the training sets described in the previous section. These nets were generated easily with the commercial package. The feedforward net trained with various modifications of the back propagation algorithm learned the training sets adequately. The training



parameters affected training time somewhat, but, as might be expected, did not affect the final performance of the trained net. Training time was not an important factor for this work. The size of the feed forward net does not increase significantly as the number of training examples increases. Fuzzy ARTMAP was also used during the May repeat of tuning run 4. This net trains quickly and performs adequately, but its size increases exorbitantly as the number of classes of shadowgraph patterns increases.

Feedforward nets had 3600 input nodes for the 60 by 60 pixel images. There were 6 outputs for the 6 tunnel parameters discussed in the previous section. There was one hidden layer containing 7 to 14 nodes. Training required between 100 and 500 presentations per training record.

A feedforward net was also trained to identify one of the 7 gross tunnel state changes only. This net uses a 1 of n code to force the winning output near unity.

As mentioned, the hybrid system for controlling operations can effectively use 10 or more nets per operation, since the software nets are fast enough. Several different types of nets might be used. The tests discussed in the next section refer only to the feedforward net.

## RESULTS AND DISCUSSION

### Sets for Testing Cascade-Tuning Nets

The best test of a neural-net sequencer is for the sequencer to identify correctly the next operating state of the tunnel during an actual run. This information could be used to automate operations. The neural nets, trained with January shadowgraph data, were not able to recognize the correct state of the tunnel when supplied with the May shadowgraph data. As mentioned, there were a number of problems, but the lack of repeatability of the shadowgraph patterns was the worst.

The next kind of test tries to determine what changes in the shadowgraph patterns will degrade the performance of the nets. A number of test sets were created for this purpose. The first test set was simply the original training set. That set determines how well the feedforward nets, or other nets, learned the training records. Next, a training record was altered to various extents, and any changes of the net's response were noted. Three test sets were created for this purpose using only degraded versions of the second point in the tuning run. The second point was recorded at an untuned condition and with the downstream Mach number indicator showing 1.46. Figure 5(b) shows the unaltered shadowgraph.

The first test set was constructed by adding various amounts of noise to the shadow graph. A noise pattern is added in amplitude proportions varying from 0 percent to 50 percent. The 50 percent case is shown in figure 6.

The second test set was constructed by changing the brightness of the shadowgraph in increments of 10 percent from -50 percent to +50 percent of the original.

The third test set was constructed by tilting the second record up to 5 degrees counterclockwise. Tilting requires some clipping of the corners of the field and the addition of some black pixels to fill in. The set is shown in figure 7.

All the test sets were created using the workstation's graphics utilities.

Other test records were created as well by scraping parts of the shadowgraph patterns at random in an image editor or by changing the number of grey levels in the image to effect changes in contrast. Two levels is the equivalent of black or white.

These records were then presented to the feedforward nets trained with the January run and the combined January and May runs. The results are presented in the next section.

### Results of Testing

Figure 8 shows the response of the feedforward net which was trained to identify only the tunnel state change. The response is to the 100 record training set itself which contains the 5 pixel shifted images

as well as the original images. There are 7 graphs for the 7 state changes. The points represent the net's response, and the lines represent the training response. Transitions to the last new state appear most often. Transitions to states 1 and 5 are next most often.

Figures 9, 10, and 11 have identical formats. Each summarizes the result of degrading the shadowgraph of the second run point with a different effect. Only the results for the vernier bypass valve and the Mach number are shown; since the effects on the other outputs are similar. The large dots in each graph show the response of the net trained with the January data only. The small dots show the response of the net trained with both the January and May data.

Figure 9 shows the result of making the shadowgraph as much as 50 percent noise. Figure 9(a) shows the effect on the neural net estimate of the valve opening. The upper line represents the training level, and the lower line is the level at which the neural net incorrectly specifies the valve state. Figure 9(b) shows the effect of noise on the neural net's estimate of Mach number. The line represents the training level.

Figure 10 shows the result of making the shadowgraph as much as 50 percent darker and 50 percent lighter than the original shadowgraph. Figure 10(a) shows the effect on the estimated valve setting, and figure 10(b) shows the effect on the Mach number. The interpretations of the outputs and levels are the same as for figure 9.

Figure 11 shows the result of tilting or rotating the shadowgraph as much as 5 degrees. Again, figure 11(a) represents the estimated valve setting; figure 11(b) represents the estimated Mach number; and the interpretations of the outputs and levels are the same as for figure 9.

The results of changing the number of shadowgraph levels from a maximum of 256 to as few as 2 levels are not shown. The effects are minor.

The results of altering the window dirt patterns in a image editor are also not shown. The effects are major.

These results are discussed in the next section.

## Discussion of Results

The neural nets were easily able to learn, or over learn, the training records. The state transition decisions represented by figure 8 are all correct and are much better than the 0.5 decision level. Some neural-net types learned the training sets faster and even better, but that apparent increment in performance provided no practical benefits for this study. The feedforward net, trained with some form of the back propagation algorithm, was adequate. The processing speed of the trained nets has already been mentioned as being excellent.

The neural nets had a decidedly mixed performance record for handling degraded images. Uniform noise, brightness changes, and changes in the number of grey levels in the image do not degrade performance. The estimates of the valve settings in figure 9 for noise and figure 10 for brightness remain above the lower limit for a correct identification of the valve state. The number of grey levels in the image was observed to have a small effect on net performance. In effect, a 2 bit image did not perform much worse than a 8 bit image.

But, small changes in the overall pattern had a serious, negative effect. Figure 11(a) shows that tilting the shadowgraph images by more than 2 to 3 degrees causes an erroneous identification of valve state. Figure 11(b) shows that the estimated Mach number drops rapidly from supersonic to subsonic as the tilt increases. The outputs will tend toward limits as tilt increases. These limits were registered throughout the May test run. The limits were essentially the same for different types of nets. The same kind of behavior occurs when the image patterns are altered in other ways. Images such as figure 5 show dirt patterns (salt streaks). Altering the dirt patterns somewhat in an image editor tends to drive the net estimates to the limits.

The failure of the neural nets to estimate the states of the May test run cannot be attributed to any single effect in the shadowgraph. Roughly, the failure was equivalent to having about a 5 degree tilt in the flow visualization. But the actual tilt error was no more than a degree or two. There was a distortion of the back wall of the tunnel between the January and May runs. The lower blade (figs. 2 and 3(b)) shifted in position about 0.125 in. (3.18 mm). The dirt patterns changed between the January and May runs. Another source of changing patterns was the flow visualization system itself. The windows, dating from the 1940's, have noticeable patterns, and these windows were removed, cleaned, and replaced frequently between January and May. The Toepler schlieren (used for shadowgraph) and its mirrors are rather ancient; the mirrors have their own patterns. The crack in the rear wall mirror was another source of a time varying pattern. The mirror was also a rear surface mirror, thereby requiring two passes through its own glass.

Combining the January and May runs for training improved slightly the tolerance of the nets for images changes. The small dots in figures 9 to 11 represent the combined training set. The curves defined by the small dots are somewhat flatter than the curves defined by the large dots for the January run only.

### CONCLUDING REMARKS

The three-blade, four-passage cascade tuning exercise was much too complicated to demonstrate neural-net automation of tunnel operations. Nevertheless, the exercise clearly defined how research, development, and applications of neural-net, as well as other parallel processing, techniques should be executed in a wind tunnel environment. The present workstation, software-net combination is much more than adequate to handle the current rate of operations. The combination is well placed to acquire flow visualization inputs, the entire set of tunnel sensor data, computational models, and eventually to advise the Modicon control system. The concept of having the parallel processing in a side loop makes it easy to incorporate and test any other approach without affecting tunnel operations. The tunnel is now much better equipped to supply inputs to the side loop. The actual sensor data system was modified extensively since the January run. Future work will be able to use pressure readings much more reliably and efficiently. The nets will be used to estimate pressure settings rather than valve settings.

The concept of using flow visualization records to control operations remains unproven. But, the requirements and setup for making that proof are better known. The neural nets easily learn the flow visualization records. The nets are very sensitive to changes in the large scale patterns, but are reasonably insensitive to noise and changes in brightness. Unfortunately, large scale patterns such as patterns created by dirt or window defects should be irrelevant to operations. In fact, the decision to note or ignore any pattern is essentially an expert decision. A feedforward net must learn to make that decision by example. Training sets must be large enough and inclusive enough to contain the relevant examples. There is evidence that increasing the training set size does reduce the sensitivity of the net to irrelevant changes of alignment of the flow visualization system. In fact, the net probably can be taught to ignore shifts and rotations of fixed patterns. Training sets can become quite large. For example, the January training set represented only 7 changes of the state of the tunnel. The actual training set included 100 records.

The failure mode of the neural networks was revealed by this work. As the flow visualization degrades, the estimated outputs tend toward those of a default state. Perhaps, a net can be trained to map irrelevant pictures onto that state. The rule based portion of the hybrid system for controlling operations can then be programmed to ignore the output of the net when that state is generated by the net.

The over sensitivity of the nets to pattern changes is a nuisance in many cases. That sensitivity also has the potential to be extremely valuable for controlling wind tunnel operations. Operations often depend critically on accurate identification of shockwave signatures. That is, there is a need to identify shockwave positions, shapes, angles, strengths, and groupings. The neural nets have the potential to change control estimates based on minute changes of these features. Our next tests will be conducted at Mach 2, and will attempt to estimate operations from shock signatures. We will attempt to minimize ex-

traneous patterns or changes in patterns by carefully aligning the flow visualization system. The patterns cannot be eliminated entirely from the ancient windows of the tunnel, so we will also test whether we can train our system of nets to identify said patterns as irrelevant.

The flow visualization so far has been shadowgraph. The setup will handle any other form of flow visualization as easily. The tunnel windows do not tolerate Toepler schlieren very well. But focusing schlieren is available. Future work on NASA priorities such as emissions may utilize fluorescence, various forms of interferometric spectroscopy, particle images, etc.

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4. Neural Works Professional II/PLUS, vended by NeuralWare, Inc. Penn Center West, Building IV, Pittsburgh, PA 15276.
5. COHU Model 4815 Solid-State Monochrome CCD Camera, vended by COHU, Inc., 5755 Kearny Villa Road, San Diego, CA 92123.
6. MODICON, vended by MODICON AEG, 1 High St., North Andover, MA 01845.

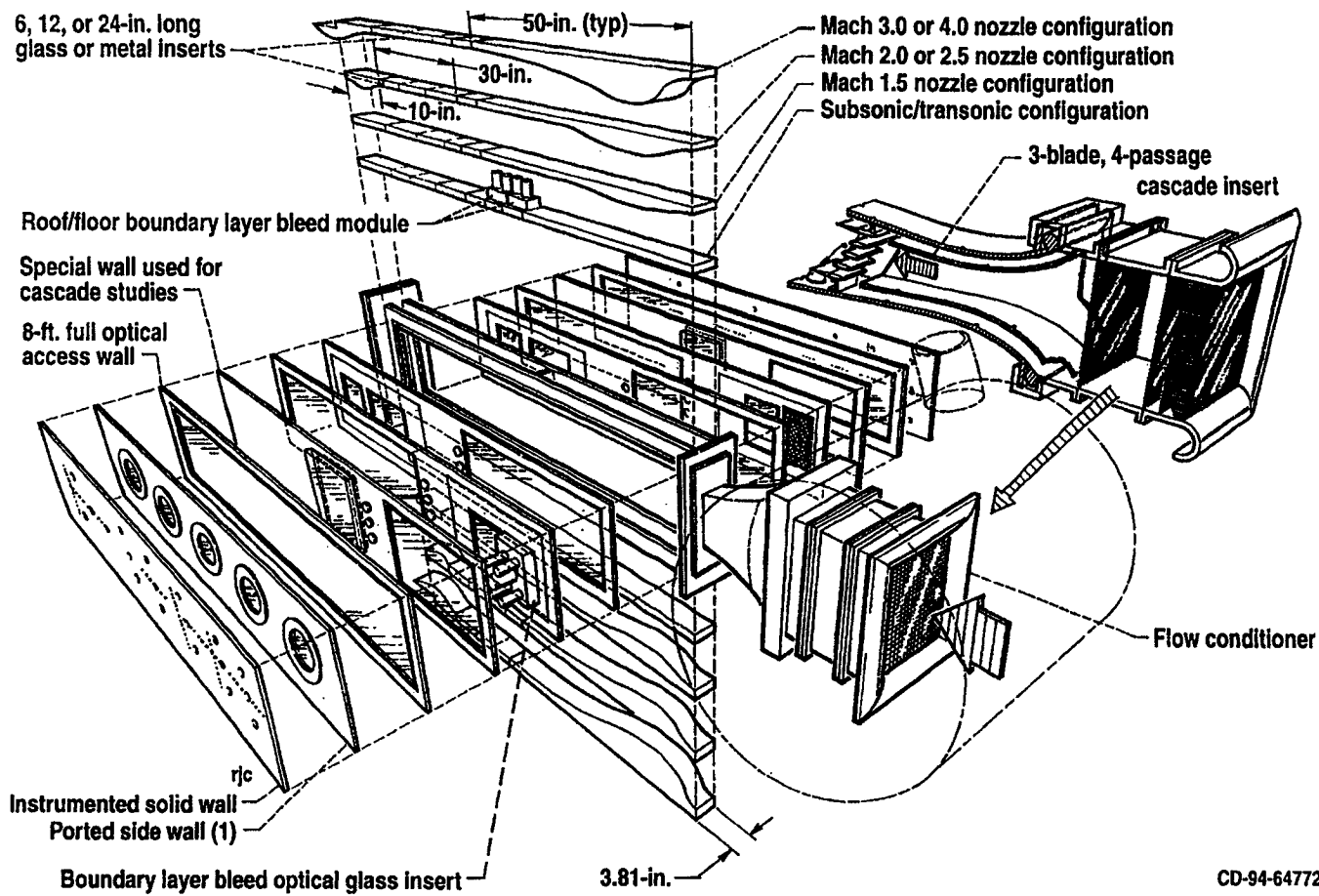


Figure 1.—Inserts for wind-tunnel altitude-exhaust duct including three-blade, four-pass cascade.

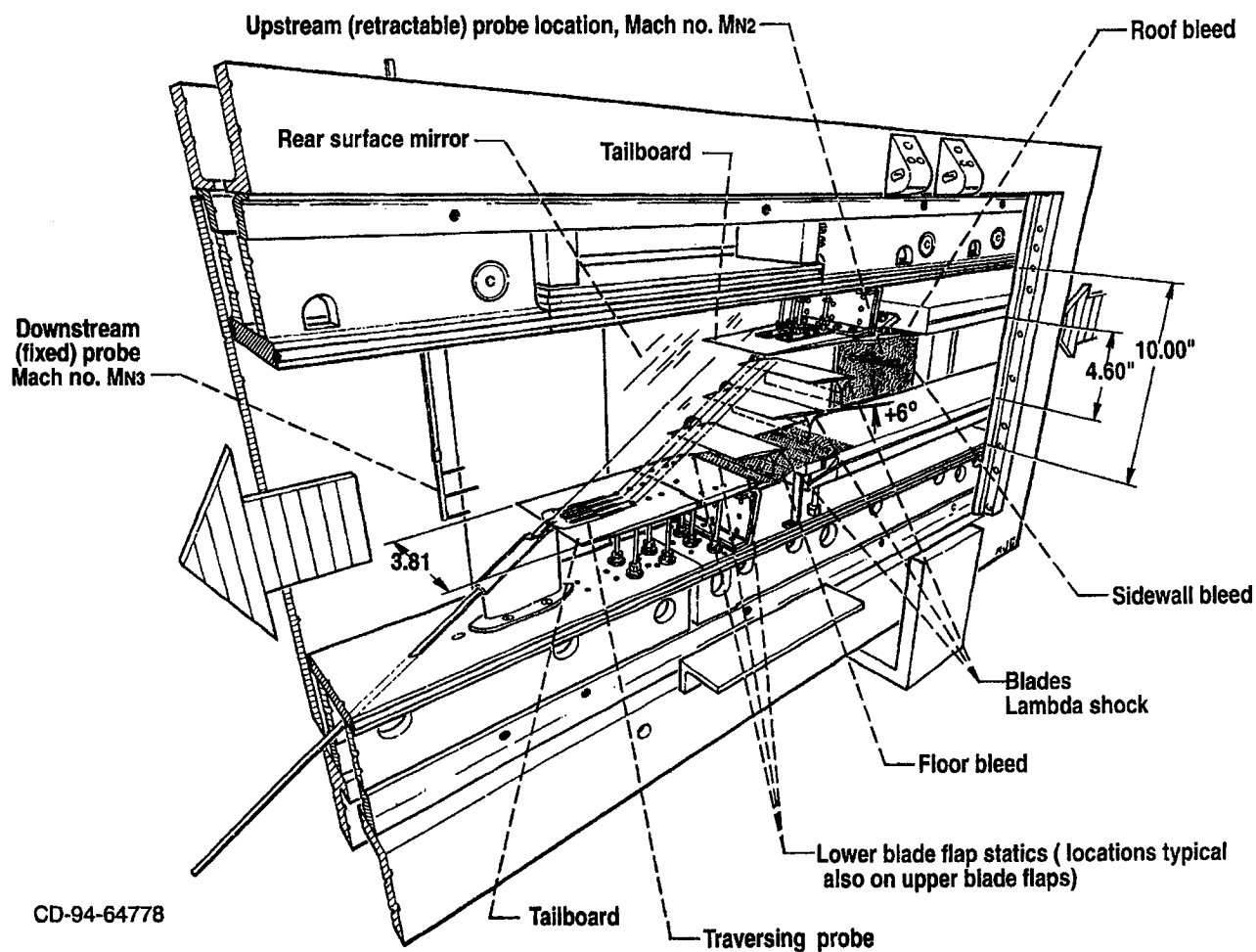
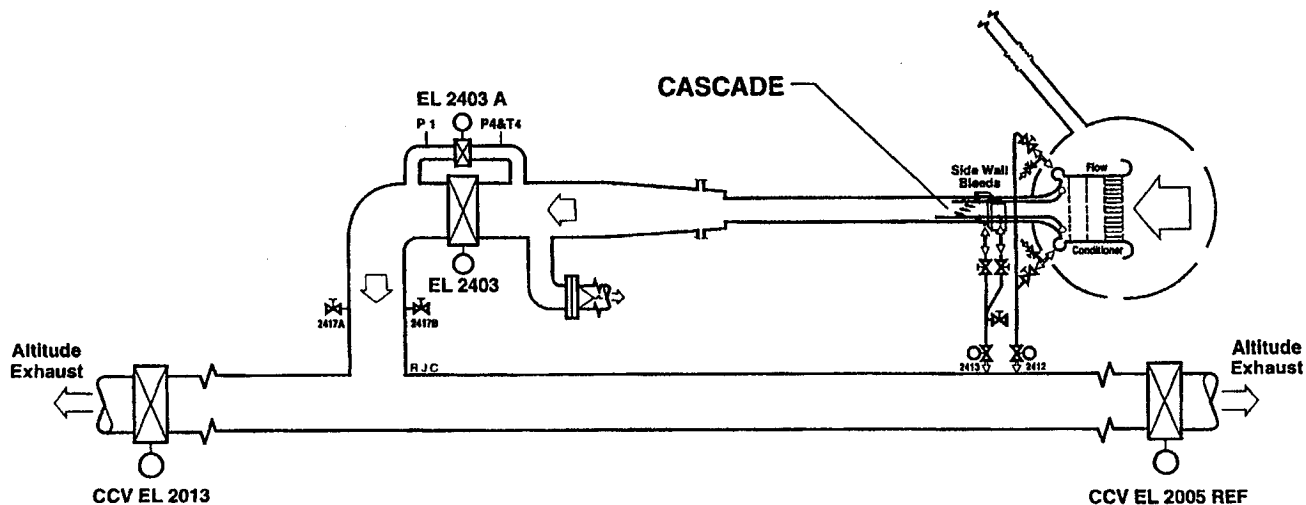
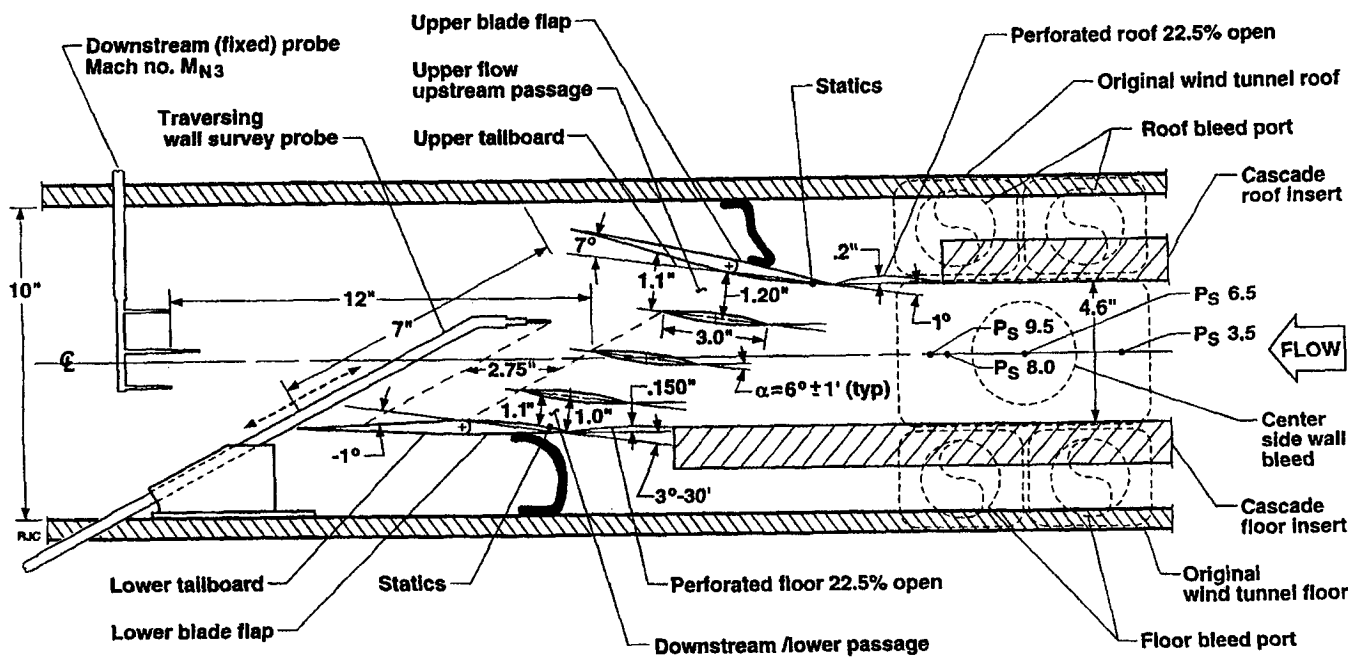


Figure 2.—Details of the cascade insert showing the bleeds, the traversing rake, and the Mach number indicator MN3.



(a)

CD-94-64775



(b)

CD-94-64774

Figure 3.—The main valve 2403 and the vernier bypass valve 2403 A appear in 3(a), and the cascade tuning parameters are depicted in 3(b).

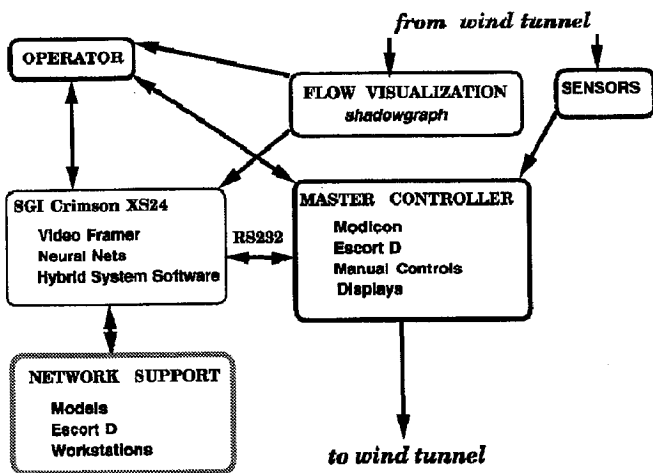


Figure 4.—Layout for controlling tunnel operations using artificial neural networks.

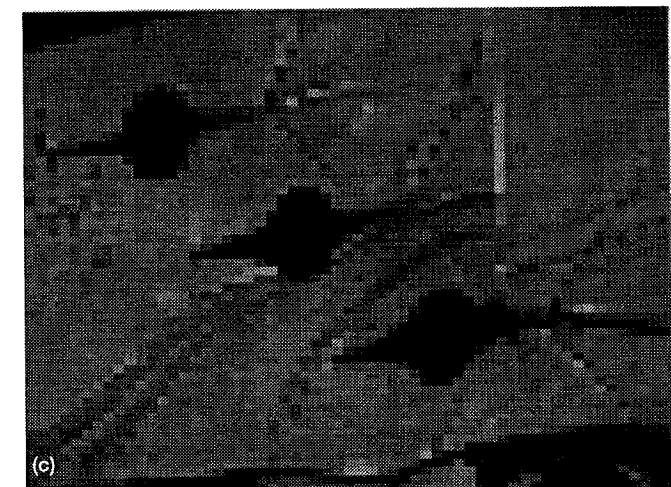
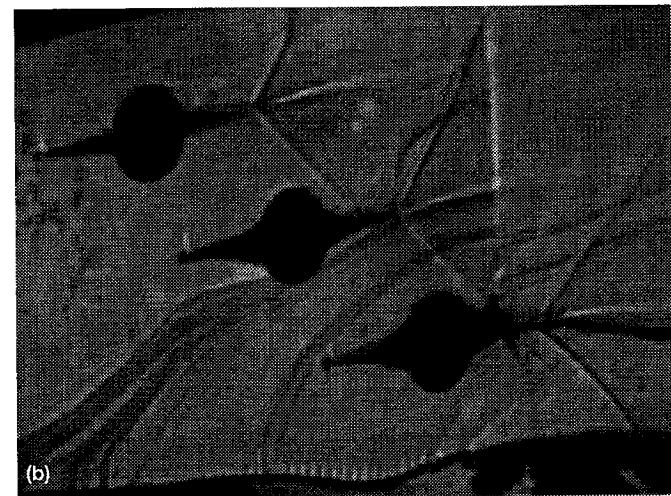
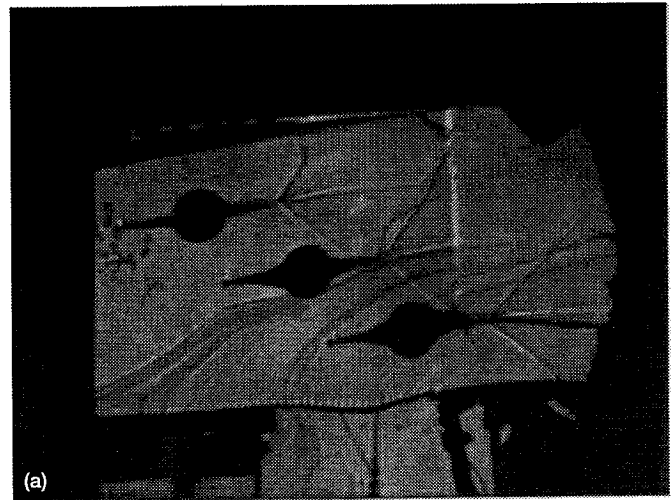


Figure 5.—Shadowgraph images for second data point of Jan. tuning run 4. (a) Shows the image from the frame grabber. (b) Shows the image after cropping. (c) Shows the image converted to 60 x 60 pixels as used by the neural nets. Mach number indicator read 1.43. Images are inverted left to right relative to the actual flow direction.



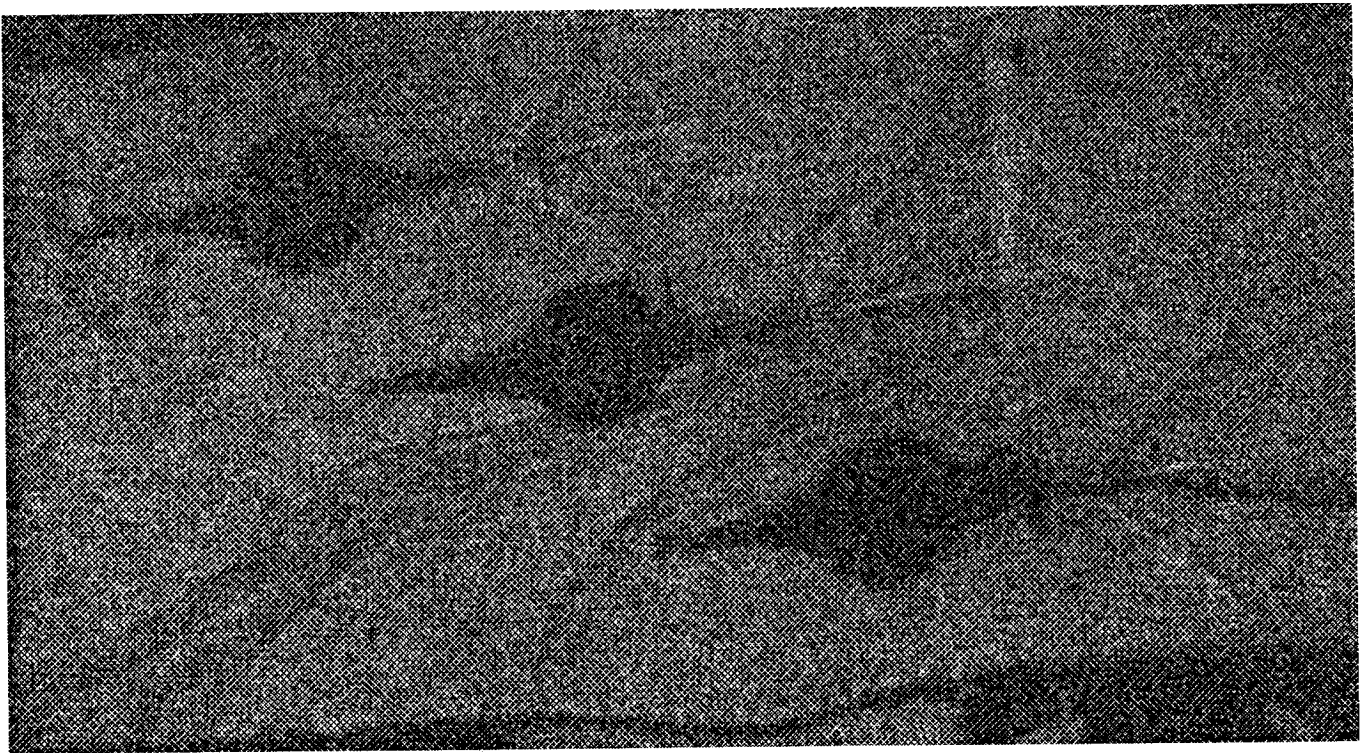
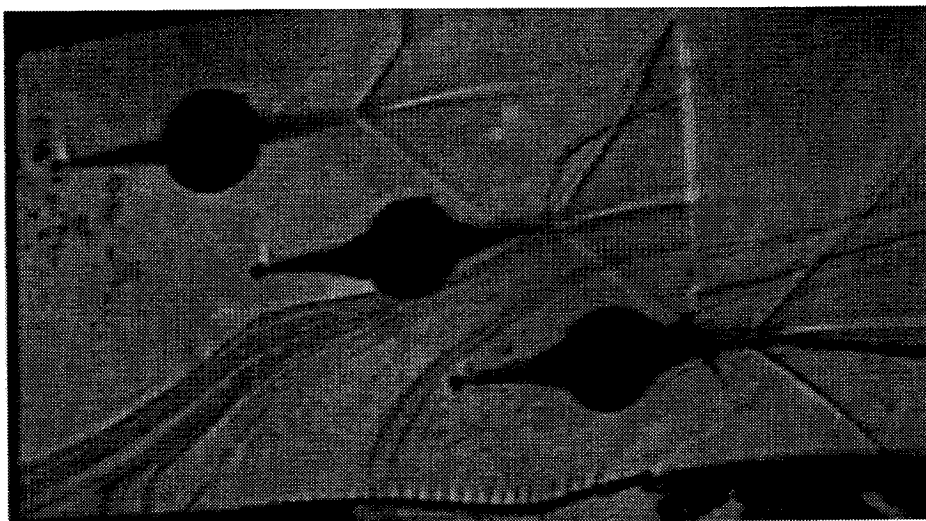


Figure 6.—Shadowgraph images from figure 5b with noise added; picture is 50 percent noise.



**0 DEGREE ROTATION**



**5 DEGREE ROTATION**

Figure 7.—Shadowgraph images from figure 5b showing two extremes of tilt or rotation; rotated images were used to test response of net to alignment errors of shadowgraph.

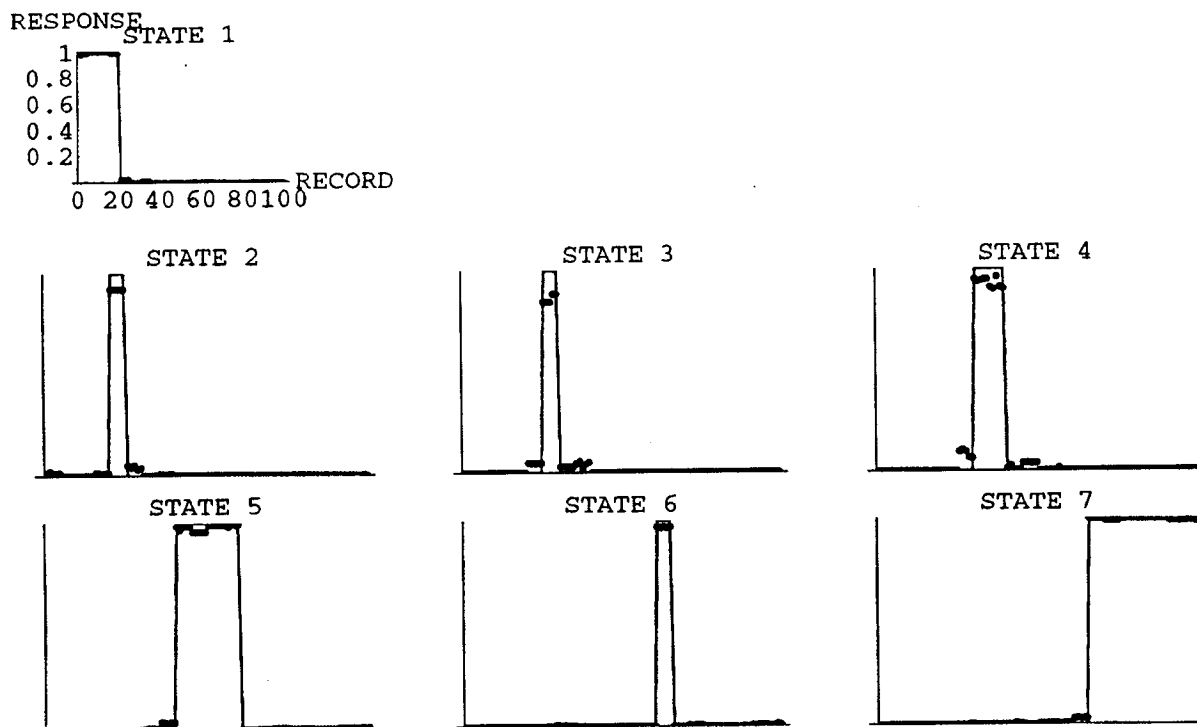


Figure 8.—Training results for Jan. training set; lines show correct transition states for different records of training set; dots show trained net's responses to records; records are numbered from 1 to 100.

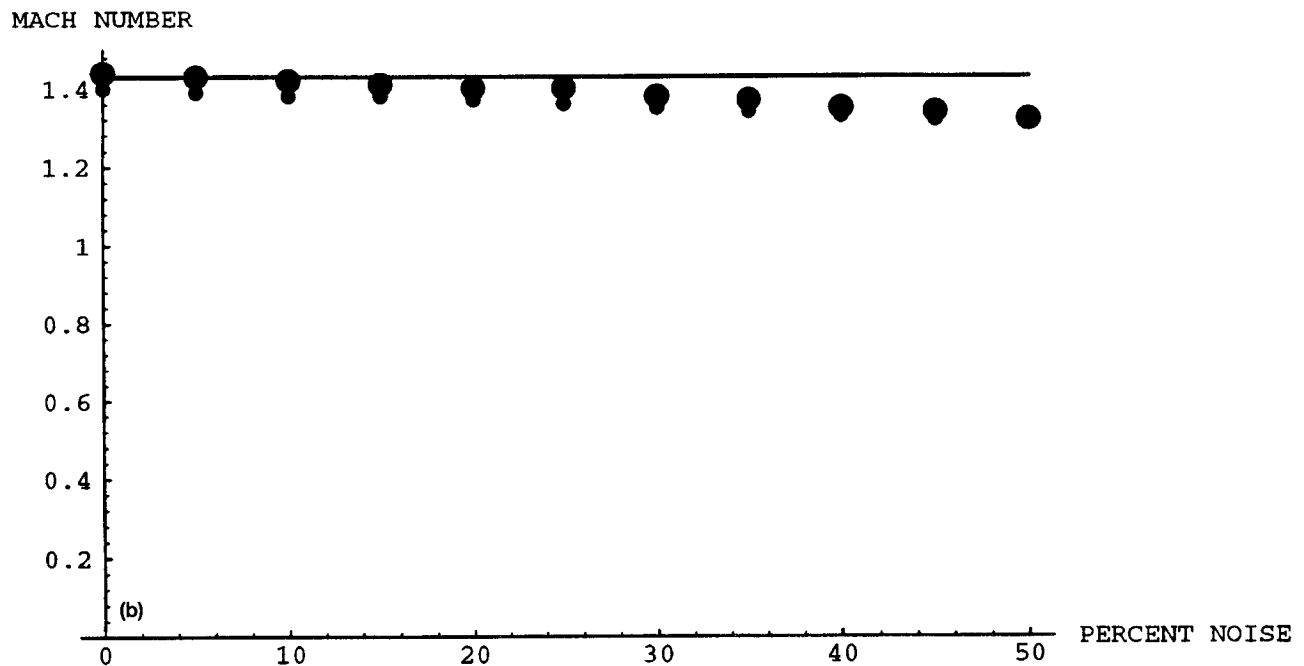
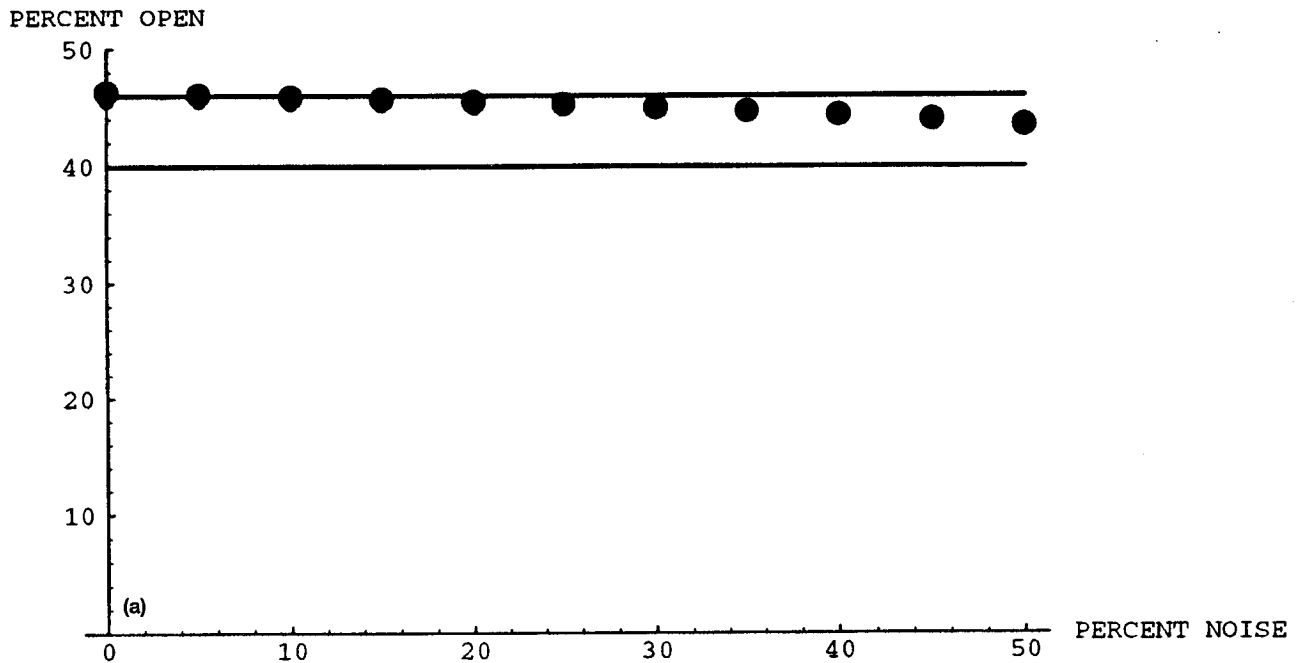


Figure 9.—Response of nets to noise; large dots represent net trained with Jan. records; small dots represent net trained with Jan. and May records. (a) Shows the estimated bypass valve opening where the upper line is the training value and the lower line is the minimum error free estimate. (b) Shows the Mach number estimates where the line is the training value.

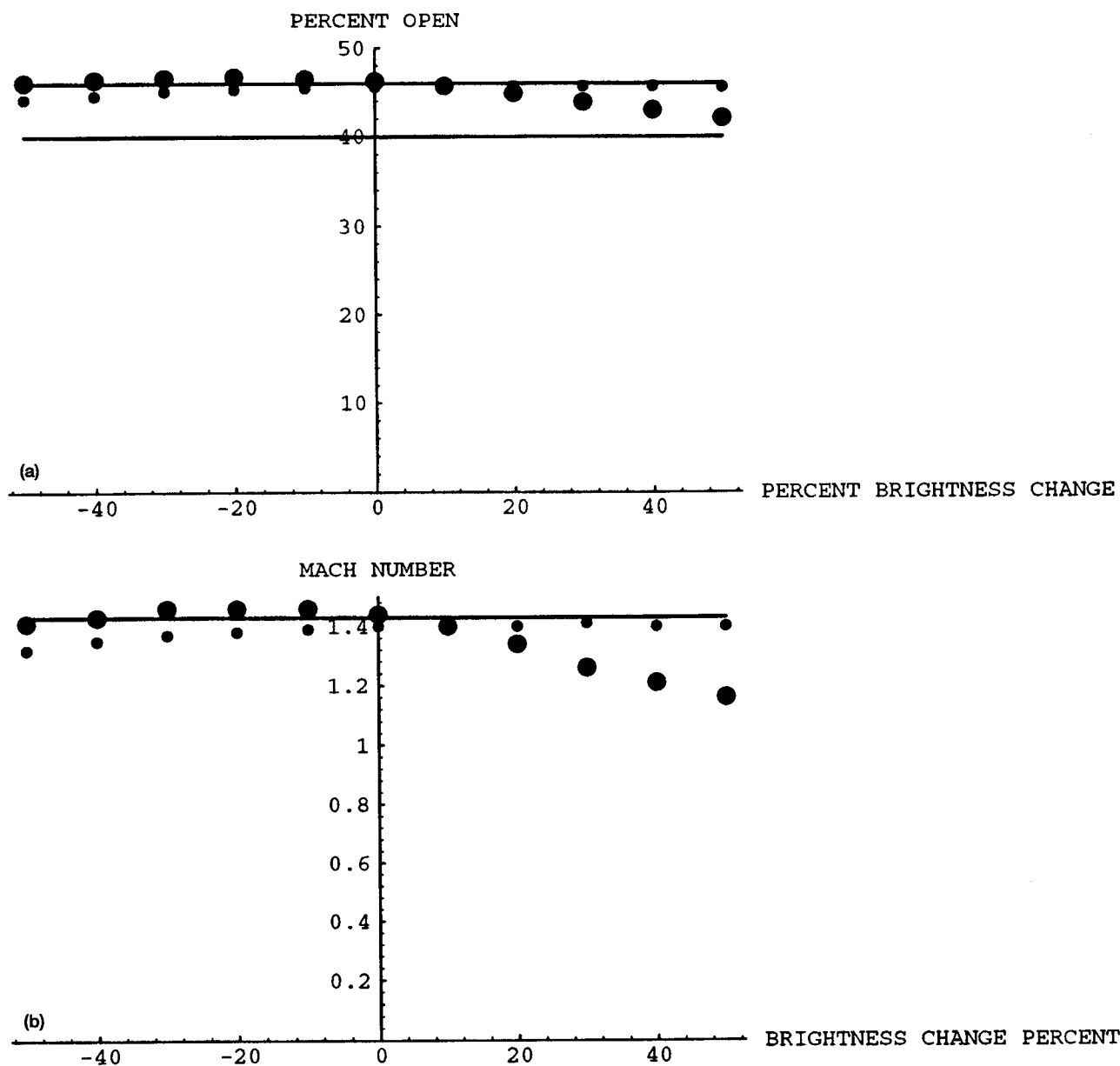


Figure 10.—Response of nets to brightness changes; lines and dots are defined as in figure 9. (a) Represents the net's estimates of the bypass valve setting. (b) Represents the nets' estimates of Mach number.

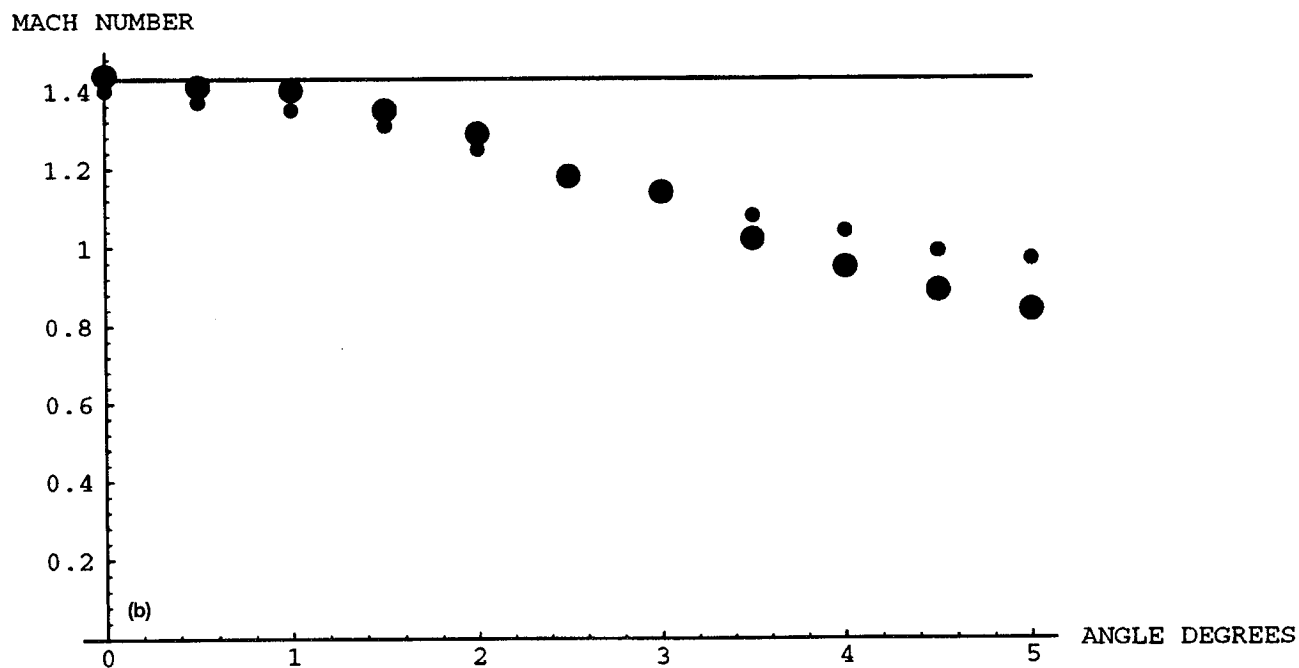
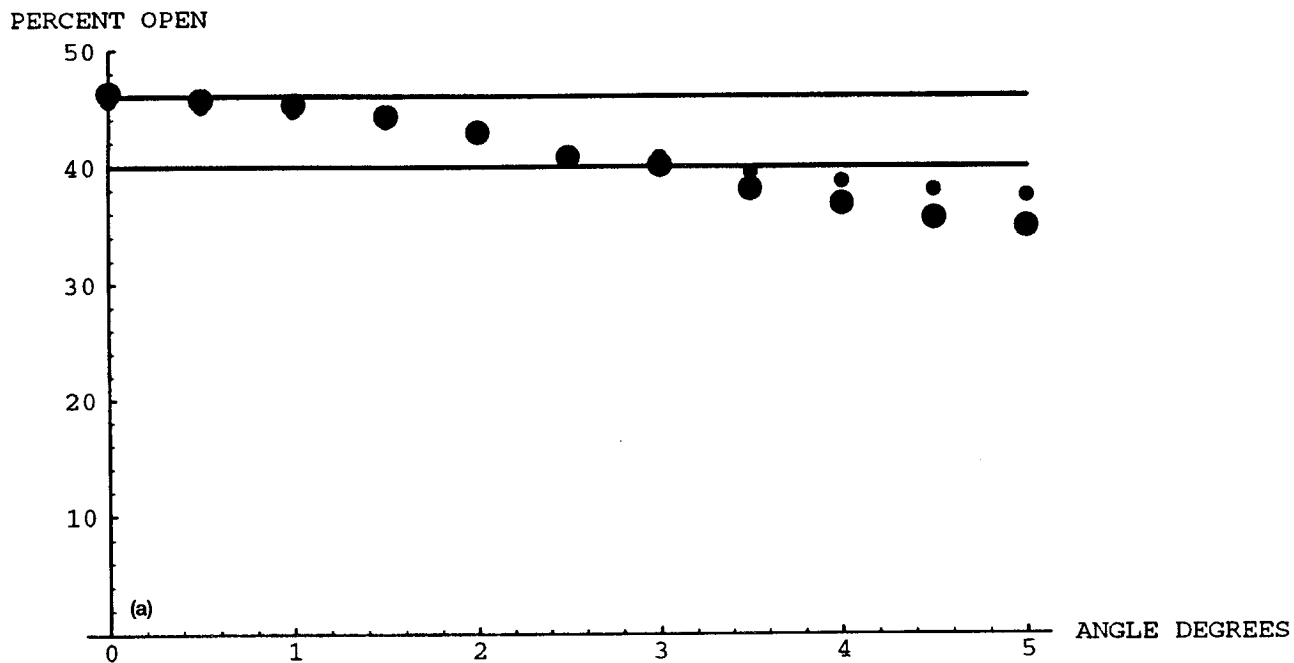


Figure 11.—Response of nets to rotation or tilt of the shadowgraph field; lines and dots are defined as in figure 9. (a) Represents the net's estimates of the bypass valve setting. (b) Represents the nets' estimates of Mach number.



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| 13. ABSTRACT (Maximum 200 words)<br><br>Neural net control of operations in a small subsonic/transonic/supersonic wind tunnel at Lewis Research Center is discussed. The tunnel and the layout for neural net control or control by other parallel processing techniques are described. The tunnel is an affordable, multiuser platform for testing instrumentation and components as well as parallel processing and control strategies. Neural nets have already been tested on archival schlieren and holographic visualizations from this tunnel as well as recent supersonic and transonic shadowgraph. This paper discusses the performance of neural nets for interpreting shadowgraph images in connection with a recent exercise for tuning the tunnel in a subsonic/transonic cascade mode of operation. That mode was operated for performing wake surveys in connection with NASA's Advanced Subsonic Technology (AST) noise reduction program. The shadowgraph was presented to the neural nets as 60 by 60 pixel arrays. The outputs were tunnel parameters such as valve settings or tunnel state identifiers for selected tunnel operating points, conditions, or states. The neural nets were very sensitive, perhaps too sensitive, to shadowgraph pattern detail. However, the nets exhibited good immunity to variations in brightness, to noise, and to changes in contrast. The nets are fast enough so that ten or more can be combined per control operation to interpret flow visualization data, point sensor data, and model calculations. The pattern sensitivity of the nets will be utilized and tested to control wind tunnel operations at Mach 2.0 based on shock wave parameters. |   |  |   |  |
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